EDITED BY
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PROGNOSTICS AND HEALTH MANAGEMENT OF ELECTRONICS

FUNDAMENTALS, MACHINE LEARNING, AND THE INTERNET OF THINGS

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Prognostics and Health Management of Electronics

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Contents

Dr. Myeongsu Kang passed away before the final publication of this book. This book is dedicated to Dr. Kang, his wife Yeoung-seon Kim, and children Mark and Matthew.

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Preface

In 2017, Toyota Motor North America recalled 28 600 model year 2018 C-HR vehicles and 39 900 model year 2012–2015 Prius Plug-In Hybrids because the electronic parking brake was malfunctioning.[1] In 2016, Samsung was forced to recall about 2.5 million Samsung Galaxy Note 7s due to lithium-ion battery malfunctions; analysts at Nomura estimated ditching the Note 7 resulted in a $9.5 billion loss in sales and the loss of $5.1 billion in profits.[2] On May 27, 2016, an engine caught fire on a Boeing 777-300 as it accelerated for take-off as Korean Air Flight 2708 at Japan's Haneda Airport.[3] The take-off was aborted, and all 17 crew members and 302 passengers were evacuated. On July 23, 2011, two high-speed trains collided on a viaduct in the suburbs of Wenzhou, Zhejiang province, China, resulting in the deaths of 40 people.[4] According to the official investigation, the accident was caused by faulty signal systems that failed to warn the second train of the stationary first train on the same track. On 22 June, 2009, a subway train-on-train collision occurred between two southbound Washington Metro trains in northeast Washington, DC. The collision was caused by a malfunction of a track circuit component, which had been suffering from parasitic oscillations that left it unable to reliably report when that stretch of track was occupied by a train.[5]

All of these incidents could have been prevented if there was health and usage monitoring, prognostics and forecasting of maintenance. Prognostics and health management (PHM) is a multifaceted discipline that protects the integrity of components, products, and systems of systems by avoiding unanticipated problems that can lead to performance deficiencies and adverse effects on safety. More specifically, prognostics is the process of predicting a system's remaining useful life (RUL). By estimating the progression of a fault given the current degree of degradation, the load history, and

1 Limbach, J. (2017). Toyota recalls C-HR and Prius Plug-In Hybrid vehicles. Consumer Affairs. Available at https://www.consumeraffairs.com/news/toyota-recalls-c-hr-and-prius-plug-in-hybrid-vehicles-111617.html (accessed February 18, 2018).

2 Mullen, J. and Thompson, M. (2016). Samsung takes $10 billion hit to end Galaxy Note 7 fiasco. CNNTech. Available at http://money.cnn.com/2016/10/11/technology/samsung-galaxy-note-7-what-next/index.html (accessed January 31, 2018).

3 McBride B. (2016). Hundreds evacuate Korean air jet after engine catches fire. ABC News. Available at http://abcnews.go.com/International/hundreds-evacuate-korean-air-jet-engine-catches-fire/story?id=39418885 (accessed January 31, 2018).

4 Wenzhou train collision. Available at https://en.wikipedia.org/wiki/Wenzhou_train_collision (accessed January 31, 2018).

5 June 2009 Washington Metro train collision. Available at https://en.wikipedia.org/wiki/June_2009_Washington_Metro_train_collision (accessed January 31, 2018).

the anticipated future operational and environmental conditions, PHM can predict when a product or system will no longer perform its intended function within the desired specifications. Health management is the process of decision-making and implementing actions based on the estimate of the state of health (SOH) derived from health monitoring and expected future use of the systems.

To address the growing interest in PHM among industry, government, and academia, *Prognostics and Health Management of Electronics* was published in 2008. The primary purpose of the book was to provide a fundamental understanding of PHM, to introduce the PHM approaches – that is, physics-of-failure (PoF), data-driven, and fusion approaches – and techniques being developed to introduce sensor systems for in situ health and usage monitoring, and to enable prognostics for electronic components, products, and systems of systems. The book discussed the determination of the implementation costs, potential cost avoidance, and the resulting return on investment (ROI) offered by PHM. Challenges and opportunities were presented for research and development in PHM of electronics.

PHM techniques have advanced and matured considerably since 2008. For example, front-loaded product launches, high-volume supply chains, shorter product life-cycles, tighter design tolerances, and relentless cost pressures in today's electronics industry are challenging the assumption that conventional practices and technologies are adequate to sustain product quality. In the Internet of Things (IoT) era, the dramatic increase of sensors, data rates, and communication capabilities continue to drive the complexity of PHM applications to new levels. As a result, electronic component and product manufacturers are looking for new insights to use the massive volume of data streaming in from their systems and sensors.

This new book is more than an update of *Prognostics and Health Management of Electronics* (2008). There are 19 new chapters, and all the previous chapters have been revamped to include the current state of the art. A summary of what each chapter covers is presented below:

Chapter 1, "Introduction to PHM", provides a basic understanding of PHM and the techniques being developed to enable prognostics for electronic products and systems and presents steps for implementing PHM in components, systems, and systems of systems. Likewise, the general approaches to electronics PHM are presented, which can be realized by the use of fuses and canary devices, monitoring and reasoning of failure precursors, and monitoring of environmental and usage loading for PoF-based stress and damage modeling. Additionally, related to the IoT era, PHM is having a significant influence on the implementation of reliability assessment, prediction, and risk mitigation, and is creating new business opportunities.

Chapter 2, "Sensor Systems for PHM", introduces the fundamentals of sensors for in-situ health and usage monitoring and their sensing principles. This chapter discusses the requirements of a sensor system for PHM, the performance needs of the sensor system, and the physical and functional attributes, reliability, cost, and availability of the sensor system. Additionally, this chapter provides a checklist to select proper sensor systems for a specific PHM application and presents emerging trends in sensor system technologies.

Chapter 3, "Physics-of-Failure Approach to PHM", provides insight into the various commonly observed failure modes and mechanisms in electronic and mechanical components/systems and presents the case for using physical/phenomenological models that might represent established failure mechanisms quite accurately. The sequence of procedures to follow for an in-depth PoF prognosis is presented, and the need for canary structures to accelerate failure for quick RUL estimation is highlighted. Several examples of PoF prognosis in microelectronic devices are presented, and the complexities involved in using PoF methods for state-of-the-art nanoelectronic devices are also described. While the PoF approach provides a mathematical construct for degradation mechanisms, the need to use data-driven Bayesian methods in conjunction with quantitative RUL prognosis is emphasized.

Chapter 4, "Machine Learning: Fundamentals", provides the basics of machine learning, which has been widely used in PHM to determine correlations, establish patterns, and evaluate data trends leading to failure. This chapter further explains machine learning algorithms to be implemented in PHM based on whether they are trained with human supervision (supervised, unsupervised, semi-supervised, and reinforcement learning); whether they can learn incrementally on the fly (online versus batch learning); and whether they work by simply comparing new data points to known data points, or instead detect patterns in the training data and build a predictive model (instance-based versus model-based learning). Additionally, this chapter provides a probability theory for better understanding of machine learning and performance metrics.

Chapter 5, "Machine Learning: Data Pre-processing", discusses the pre-processing of data that needs to precede the development of data-driven PHM methods. The pre-processing tasks discussed include data cleaning, normalization, feature extraction, feature selection, feature learning, and imbalance data management. More specifically, this chapter identifies conventional and state-of-the-art data pre-processing algorithms widely used in PHM and provides the theoretical background of each algorithm.

Chapter 6, "Machine Learning: Anomaly Detection", provides a basic understanding of anomaly detection. This chapter identifies machine learning algorithms for anomaly detection that can be classified into five categories: distance-, statistics-, model-, clustering-, and unsupervised and semi-supervised learning-based anomaly detection. This chapter briefly explains how the algorithms are employed in PHM.

Chapter 7, "Machine Learning: Diagnostics and Prognostics", presents the role of diagnostics in PHM. This chapter identifies machine learning algorithms for diagnostics and discusses the algorithms from a technical point of view. It also presents the usefulness of feature learning-powered diagnosis using deep learning. Likewise, this chapter presents the prognostics concept and provides an overview of various prognosis methods, such as regression- and filter-based methods.

Chapter 8, "Uncertainty Representation, Quantification, and Management in Prognostics", analyzes the significance, interpretation, quantification, and management of uncertainty in prognostics, with an emphasis on predicting the RUL of engineering systems and components. In order to facilitate meaningful prognostics-based decision-making, it is important to analyze how the sources of uncertainty affect prognostics and thereby compute the overall uncertainty in the RUL prediction. However, several state-of-the-art industrial techniques do not consider a systematic approach to the treatment of uncertainty. This chapter explains the importance of uncertainty representation, quantification and management in prognostics, focusing both on testing-based life prediction and condition-based prognostics. It has been demonstrated that uncertainty quantification in RUL predictions needs to be approached as an uncertainty propagation problem that can be solved using a variety of statistical methods. Several uncertainty propagation methods are explained in detail, and numerical examples are presented. Finally, practical challenges pertaining to uncertainty quantification and management in prognostics are discussed.

Chapter 9, "PHM Cost and Return on Investment", discusses the development of business cases to support the inclusion of PHM within systems. This chapter develops and demonstrates a ROI analysis for using PHM in a system. To support the ROI calculation, an overview of the investment costs and the cost returns (cost avoidances) that are possible from PHM is presented. Methods of quantifying the various costs are provided, and an ROI analysis for an avionics subsystem is developed as a case study.

Chapter 10, "Valuation and Optimization of PHM-Enabled Maintenance Decisions", discusses costs in the context of maintenance value and optimal decision-making. Value can be realized at several levels depending on the system and its stakeholders. System-level value means taking action to keep an individual system safe or to minimize the individual system's life-cycle cost. Alternatively, value can be realized at the "enterprise level" where the optimal action(s) are based on the RULs from all the members of the enterprise (e.g. a population of systems). This chapter concludes with a case study that uses the forecasted RUL of a system to obtain actionable value through valuation and optimization of predictive maintenance (PdM) decisions.

Chapter 11, "Health and Remaining Useful Life Estimation of Electronic Circuits", discusses a kernel-based method for estimating the degradation in health of an electronic circuit due to the presence of a parametric fault. The chapter also includes a statistical filter-based method to predict circuit failures, where the overall circuit degradation model is designed to include PoF-based models for the degrading component.

Chapter 12, "PHM-based Qualification of Electronics", discusses the electronic products qualification methodologies used in industry. The chapter describes the stages of product qualification from the design phase to final certification. The key considerations for qualification, such as product market segment/customer use conditions, supply chain, and environmental regulations, are explained. The chapter provides an overview of the product qualification approaches: standards-based qualification, knowledge-based qualification, and PHM-based qualification. Standards-based qualification is based on a predefined set of reliability requirements that leverage the historical database of use conditions and reliability data. Knowledge-based qualification uses key technology attributes and failure-mode-specific reliability models to provide a qualification approach tailored to the specific use condition. Prognostics-based qualification uses the product use life data to develop data-driven diagnostic and fusion prognostics techniques to monitor SOH and provide advance warning of failure.

Chapter 13, "PHM of Li-ion Batteries", presents an overview of the PHM techniques used for states estimation and RUL prediction of Li-ion batteries. The growing application of Li-ion batteries as energy storage systems has led to concern for their reliability and safety. Li-ion batteries represent complex electrochemical–mechanical systems; hence, modeling them using physics-based techniques can be computationally intensive. This chapter mainly focuses on data-driven battery modeling methods for online estimation and prediction applications. Three case studies on battery state of charge (SOC) and SOH estimation and RUL prediction are discussed in this chapter with detailed model development and validation steps.

Chapter 14, “PHM of Light-Emitting Diodes”, provides an overview of prognostic methods and models that have been applied to both light-emitting diode (LED) devices and LED systems. These methods include statistical regression, static Bayesian networks, Kalman filtering, particle filtering, artificial neural networks, and physics-based methods. The general concepts and key features of these methods, the pros and cons of applying these methods, as well as case studies of LED application, are presented. There is also a return-on-investment (ROI) discussion of using a PHM maintenance approach in LED lighting systems, compared with the unscheduled maintenance approach.

Chapter 15, “PHM of Healthcare”, presents the integration of medical devices with PHM technology to tackle reliability, safety, and life-cycle costs. As the pioneering work in this new multidisciplinary area, this chapter establishes the foundational principles for innovation in PHM of implantable medical devices, and paves the way for a PHM-based healthcare industry. Reviewed topics include the current context of medical device safety, reliability, and life-cycle cost considerations; PHM techniques and potential life-cycle benefits applicable to medical devices; and PHM needs in unmanned systems for commercial healthcare and home care for the elderly.

Chapter 16, “PHM of Subsea Cables”, introduces the reader to the area of subsea power cables, outlining their critical role in supporting the global offshore renewable energy sector. The design and verification standards of these products are summarized, and the challenges in their health management are presented via a failure mode mechanism and effect analysis from 15 years of historical industrial data. A state-of-the-art review into monitoring technologies for subsea power cables reveals that over 70% of failure modes are not monitored. To address this challenge, a fusion-based PHM approach is described that incorporates the advanced features of both the data-driven approach and the PoF-based approach in order to estimate the RUL of the cable. The model supports RUL prediction, localization of vulnerable cable zones, comparison of cable products for a given route, as well as route optimization. This study demonstrates the significant value of PHM methods for critical infrastructure.

Chapter 17, “Connected Vehicle Diagnostics and Prognostics”, describes a general framework, known as an automatic field data analyzer, and related algorithms that analyze large volumes of field data, and promptly identify root causes of faults by systematically making use of signal processing, machine learning, and statistical analysis approaches. Eventually the fault analysis results are provided to product development engineers with actionable design enhancement suggestions. The vehicle battery failure analysis of two years of data from 24 vehicles is performed to demonstrate the effectiveness of the proposed framework. This work is particularly critical to the vehicle manufacturing industry for enhancing product quality and reliability, where new vehicle subsystems are rapidly introduced with increasing complexity.

Chapter 18, “The Role of PHM at Commercial Airlines”, provides an overview of how PHM evolved from scheduled maintenance practices to becoming an integral part of planned maintenance at commercial airlines. As sensor and data acquisition technologies advanced and more aircraft were equipped with these technologies, the benefits of PHM expanded beyond that of improved aircraft availability, reduced maintenance costs, and increased operational safety. Various stakeholders began to compete for data rights and ownership, slowing the progress of PHM implementation and integration. This chapter discusses the evolution of maintenance strategies, the goals of the various stakeholders, the implementation of PHM, and the applications of PHM at commercial airlines from its beginnings to today.

Chapter 19, "PHM Software for Electronics", introduces PHM software developed by the Center for Advanced Life Cycle Engineering (CALCE). The simulation-assisted reliability assessment (SARA) software was developed to conduct virtual qualification and testing of electronic products. Likewise, data-driven PHM software executes a series of data analysis and machine learning algorithms that can be used to initially understand the data and, if desired, build models to detect any deviation from required, expected, or desired performance of the object system, to determine the location of the fault (fault isolation), identify the type of fault (fault identification), and predict RUL. This chapter primarily discusses the aforementioned CALCE software.

Chapter 20, "eMaintenance", introduces a history of eMaintenance, defined as a system or framework that enhances the efficiency and effectiveness of the maintenance process by applying information and communication technologies for the provision of analytics to assist PHM and also by providing capabilities for monitoring, diagnostics, prognostics, and prescription. Further, this chapter presents technological approaches to eMaintenance and introduces applications of eMaintenance, which are a set of decision support services designed to achieve business excellence in industry.

Chapter 21, "Predictive Maintenance in the IoT Era", provides an introduction to IoT-driven PdM methodology. An overview of IoT and its applicability via connected machines to a successful PdM program is presented. This chapter highlights the challenges in traditional maintenance techniques and explores the opportunities for PdM. Instead of letting a component run to failure or replacing a healthy component because it is due based on the preventative maintenance interval, PdM can help organizations make repairs only at the optimum time when it is truly needed. This chapter delves into a few key IoT-based PdM cases, and provides an overview of different machine learning methodologies that leverage streaming of real-time data from machines in order to assess in-service machine health and future system failures. The chapter then covers some best practices for implementing a PdM program, with insights into the challenges and some potential strategies to mitigate the same.

Chapter 22, "Analysis of PHM Patents for Electronics", reviews and analyzes PHM-related US patents to explore the trends, challenges, and opportunities for PHM of electronics in a variety of industries. Because most review papers currently available on the subject are academic papers published in journals, this review and analysis of patents fills the gap by providing different viewpoints between academia and industry on the subject.

Chapter 23, "A PHM Roadmap for Electronics-Rich Systems", presents the challenges and opportunities for research and development in PHM of electronics. Included are recommendations on the essential next steps for continued advancement of PHM technologies, and a PHM technology roadmap is presented.

Appendix A, "Commercially Available Sensor Systems for PHM", provides descriptions and specifications for sensor systems that are currently commercially available for PHM.

Appendix B, "Journals and Conference Proceedings Related to PHM", offers a list of journals and conference proceedings where PHM-related articles are published. The list covers methods and applications in civil and mechanical structures, avionics, mechanical and electronic products, prognostic algorithms and models, sensors, sensor application, health monitoring, prognostics-based maintenance, and logistics.

Appendix C, "Glossary of Terms and Definitions", provides a glossary of the most relevant terms and definitions, in particular those used in this volume.

This book is indispensable for engineers and data scientists in design, testing, operation, manufacturing, and maintenance. It covers all areas of electronics, and provides guidance to:

- assess methods for damage estimation of components and systems due to field loading conditions;
- assess the cost and benefits of prognostic implementations;
- develop novel methods for in-situ monitoring of products and systems in actual life-cycle conditions;
- enable condition-based (predictive) maintenance;
- increase system availability through an extension of maintenance cycles and/or timely repair actions;
- obtain knowledge of load history for design, qualification, and root cause analysis;
- reduce the occurrence of no-fault-found diagnostics;
- subtract life-cycle costs of equipment from a reduction in inspection costs, downtime, and inventory;
- understand statistical techniques and machine learning methods used for diagnostics and prognostics;
- understand the synergy between IoT, machine learning, and risk assessment; and
- provide guidance and direction for further research and development.

Furthermore, due to the large amount of published work on PHM, any assessment inevitably leaves out some organizations and topics that we either were not aware of or did not consider relevant in the context of this book. Lastly, we would like to express our profound gratitude to the over 150 companies and organizations that support CALCE, and gave valuable, constructive and thoughtful reviews of this book.

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List of Abbreviations

2D SPRT	two-dimensional sequential probability ratio test
3D TIRF	three-dimensional telemetric impulsion response fingerprint
A/D	analog-to-digital
A4A	Airlines for America
AC	alternating current
AdaBoost	adaptive boosting
ADAS	advanced driver-assistance system
ADASYN	adaptive synthetic sampling
ADT	accelerated degradation test
AEC	aluminum electrolytic capacitor
AF	acceleration factor
AFDA	automatic field data analyzer
AI	artificial intelligence
AISC-SHM	Aerospace Industry Steering Committee on Structural Health Management
AIST	Advanced Industrial Science and Technology
ALT	accelerated life test
AMM	aircraft maintenance manual
ANN	artificial neural network
AOG	aircraft on ground
API	application programming interface
APU	auxiliary power unit
ARC	Ames Research Center
ARIMA	auto-regressive integrated moving average
ASG	APU starter generator
ATA	Air Transport Association
ATU	autotransformer unit
AUC	area under the ROC curve
BBN	Bayesian belief network
BCU	battery control unit
BGA	ball grid array
BIOS	basic input/output system
BIT	built-in test
BMC	Bayesian Monte Carlo
BMS	battery management system

BMU	best matching unit
BN	Bayesian network, batch normalization
BOP	blowout preventer
BP	back propagation
BPF	bandpass filter
BPNN	back-propagation neural network
C2MS	corrosivity monitoring systems
CABGA	ChipArray® ball grid array
CALCE	Center for Advanced Life Cycle Engineering
CAMP	continuous airworthiness maintenance program
CAN	controller area network
CAP	capacitance
CART	classification and regression tree
CASS	continuous analysis and surveillance
CBA	cost–benefit analysis
C-BIT	continuous BIT
CBM	condition-based maintenance
CBM+	condition-based maintenance plus
CCA	circuit card assembly
CC-SMPS	constant-current switch mode power supply
CCT	correlated color temperature
CDF	cumulative distribution function
CE	cross-entropy
CfA	contract for availability
CFR	Code of Federal Regulations
CHD	coronary heart disease
CL	confidence limit
CME	coefficient of moisture expansion
CMMS	computerized maintenance management system
CMOS	complementary metal-oxide-semiconductor
CND	cannot duplicate
CNI	communication navigation and identification
CNN	convolutional neural network
CoV	coefficient of variation
CPC	Cooperative Patent Classification
CPCP	corrosion prevention and control program
CPU	central processing unit
CRI	color rendering index
CSD	constant speed drive
CSP	chip scale packaging
CTE	coefficient of thermal expansion
CUT	circuit under test
CVDP	connected vehicle diagnostics and prognostics
DAG	directed acyclic graph
DC	direct current
DCF	discounted cash flow
DD	data-driven

DfR	design-for-reliability
DMU	data management unit
DOD	domestic object damage
DOF	designated overhaul facilities
DPM	defects per million
DRN	deep residual network
DRU	depot-replaceable unit
DSS	distributed strain sensing
DST	distributed strain and temperature; dynamic stress testing
DT	decision tree
DTPS	drive train prognostics systems
DTS	distributed temperature sensing
DWT	discrete wavelet transform
ECC	error checking and correction
ECEM	energy and condition monitoring
ECM	engine condition monitoring
ECRI	Emergency Care Research Institute
ECS	environmental control system
ECU	electronic control unit, engine control unit
ED	electrical driver; Euclidean distance
EDL	integrated electronic data log
EEEU	end-effector electronics unit
EEPROM	electrically erasable programmable read-only memory
EF	enhancement factor
EFV	expeditionary force vehicle
EGT	exhaust gas temperature
EHM	engine health management/monitoring
EHSA	electrohydraulic servo-actuator
EIA	Electronics Industries Alliance
EKF	extended Kalman filter
ELIMA	Environmental Life-Cycle Information Management and Acquisition
EM	expectation maximization
EMA	electromechanical actuator
EMMS	eMaintenance management system
EOA	Expert-on-Alert
EOD	end of discharge
EOL	end of life
EPC	energy performance contracting
EPR	extended producer responsibility; ethylene propylene rubber
ES	expert system; Euclidean space
ESC	enhanced self-correcting
ESD	electrostatic discharge
ESR	equivalent series resistance
ETOPS	extended operations
EV	electric vehicle
EVN	European vehicle number
FAA	Federal Aviation Authority

FADEC	full authority digital electronic control
FAR	Federal Aviation Regulations
FAT	factory acceptance test
FBG	fiber Bragg grating
FCM	fuzzy c-means clustering
FCU	fuel control unit
FD&C	Federal Food, Drug, and Cosmetic
FDA	Food and Drug Administration
FEA	finite element analysis
FFNN	feed-forward neural network
FIELD	FANUC's Intelligent Drive Link Drive
FIM	fault isolation manual
FL	fuzzy logic
FMEA	failure modes and effects analysis
FMECA	failure mode, effect and criticality analysis
FMMEA	failure modes, mechanisms, and effects analysis
FN	false negative
FOD	foreign object damage
FP	false positive
FPM	fusion prognostic model
FPR	false positive rate
FPT	first passage time
FT	fault tree
FUDS	federal urban driving schedule
GA	general aviation
GCU	generator control unit
GMM	Gaussian mixture model
GPA	gas-path analysis
GPR	Gaussian process regression
GPS	global positioning system
GPU	graphic processor unit
GUI	graphic user interface
HALT	highly accelerated life testing
HDD	hard disk drive
HDFS	Hadoop Distributed File System
HFS	hybrid feature selection
HI	health indicator
HM	health monitoring
HMM	hidden Markov model
HPF	high-pass filter
HPS	high-pressure sodium
HRT	hormone replacement therapy
HTOL	high-temperature operating life
HVAC	high-voltage alternating current
HVDC	high-voltage direct current
I2C	inter-integrated circuit
I-BIT	interruptive BIT

IC	integrated circuit; internal combustion
ICD	implantable cardioverter defibrillator
ICT	information and communication technologies
IDE	integrated data environment
IDG	integrated drive generator
IEEE	Institute of Electrical and Electronics Engineers
IESNA	Illuminating Engineering Society of North America
IFF	identification friend or foe
iForest	isolation forest
IFSD	inflight shutdown
IGBT	insulated gate bipolar transistor
i.i.d.	independent and identically distributed
IIoT	Industrial Internet of Things
ILR	implantable loop recorder
ILS	integrated logistics support
ILT	inventory lead time
iNEMI	International National Electronics Manufacturing Initiative
INS	inertial navigation system
IoT	Internet of Things
IP	intellectual property
IPC	Institute for Printed Circuits
IR	infra-red
ISHM	integrated systems health management
ISO	International Organization for Standardization
IT	Internet technology
ITO	indium tin oxide
iTree	isolation tree
IVHM	integrated vehicle health management
JEDEC	Joint Electron Device Engineering Council
JSF	Joint Strike Fighter
JTAG	joint test action group
KBQ	knowledge-based qualification
KDD	knowledge discovery in databases
KF	Kalman filtering
kLDA	kernel linear discriminant analysis
k-NN	k-nearest neighbor
KPCA	kernel-PCA
KPI	key performance indicator
K–S	Kolmogorov–Smirnov
LASSO	least absolute shrinkage and selection operation
LAV	light armored vehicle
LCC	life-cycle cost
LCEP	life-cycle environmental profile
LCM	life consumption monitoring
LDA	linear discriminant analysis
LED	light-emitting diode
LEE	light extraction efficiency

LLP	life-limited part
LPF	low-pass filter
LPP	locality preserving projection
LRU	line-replaceable unit
LS	logistics support
LSM	least-squares method
LSR	least-squares regression
LS-SVM	least-squares support vector machine
LTE	long-term evolution
MA	maintenance analytics
MAD	median absolute deviation
MAE	mean absolute error
MAP	maximum a posteriori estimation
MAR	missing at random
MCAR	missing completely at random
MCC	Matthews correlation coefficient
MCP	multichip processor
MCS	Monte Carlo simulation
MCU	module control unit
MD	Mahalanobis distance
MDC	motor-driven compressor
MEL	minimum equipment list
MEMS	microelectromechanical system
MFD	multifunction display
ML	machine learning
MLCC	multilayer ceramic capacitor
MLDT	mean logistics delay time
MLE	maximum likelihood estimation
MLP NN	multilayer perceptron neural network
MNAR	missing not at random
MOCVD	metal–organic chemical vapor deposition
MOSFET	metal-oxide-semiconductor field-effect transistor
MQE	minimum quantization error
MQW	multi-quantum well
MRO	maintenance, repair, overhaul
MSE	mean squared error
MSET	multivariate state estimation technique
MTBF	mean time between failure
MTE	molecular test equipment
MTTF	mean time to failure
MTTR	mean time to repair
NASA	National Aeronautics and Space Administration
NDT	nondestructive testing
NEA	nitrogen-enriched air
NEMS	nanoelectromechanical system
NFF	no fault found
NGS	nitrogen generation system

NHTSA	National Highway and Transportation Safety Administration
NLME	nonlinear mixed-effect estimation
NLS	nonlinear least squares
NMEA	National Marine Electronics Association
NN	neural network
NPV	net present value
NTF	no-trouble-found
NVRAM	nonvolatile random access memory
O&M	operation and maintenance
OAA	one-against-all
OAO	one-against-one
OBD	onboard diagnostics
OBIGGS	onboard inert gas generation
OC-SVM	one-class SVM
OCV	open-circuit voltage
OEM	original equipment manufacturer
OHVMS	offshore high-voltage network monitoring system
OOR	ordered overall range
OT	optimizing technology
PAR	Precision Approach Radar
PBL	performance-based logistics
PBSA	performance-based service acquisition
Pc-	phosphor-converted
PCA	principal component analysis
PCB	printed circuit board
PCC	Pearson correlation coefficient
PCN	product change notification
PCS	principal component space
PD	partial discharge
pdf	probability density function
PdM	predictive maintenance
PF	particle filter
PH	proportional hazard
PHM	prognostics and systems health management
PI	performance indicator
PLC	programmable logic controller
pmf	probability mass function
PMML	Predictive Maintenance Markup Language
POE	power over Ethernet
PoF	physics-of-failure
PPA	power purchase agreement
PPP	public/private partnership
PSO	particle swarm optimization
PSS	product service system
PTH	plated through hole
PWB	printed wiring board
QCM	quiescent current monitor

QW	quantum well
RAMS	reliability, availability, maintainability, and supportability
RBF	radial basis function
RBFNN	radial basis function neural network
RBU	residual building unit
RC	resistance/capacitance
RCM	reliability-centered maintenance
ReLU	rectifier linear unit
RESS	rechargeable energy storage system
RF	radio frequency
RFID	radio frequency identification
RH	relative humidity
RLA	remaining life assessment
RM&D	remote monitoring and diagnostics
RMSE	root-mean-squared error
RNN	recurrent neural network
ROA	real options analysis
ROC	receiver operating characteristic
RoHS	Restriction of Hazardous Substances
ROI	return on investment
ROM	read-only memory
ROV	remotely operated underwater vehicle
RPN	risk priority number
RTD	resistance temperature detector
RTOK	re-test OK
RTPH	real time-power harness
RUL	remaining useful life
RUP	remaining useful performance
RVM	relevance vector machine
SA	simulated annealing
SAAAA	sense, acquire, analyze, advise, and act
SaaS	Software as a Service
SAE	Society of Automotive Engineers
SAR	socially assistive robotics
SARA	Simulation-Assisted Reliability Assessment
SATAA	sense, acquire, transfer, analyze, and act
SBCT	Stryker Brigade Combat Team
SBQ	standards-based qualification
SCADA	supervisory control and data acquisition system
SD	secure digital; standard deviation
SDG	signed diagraph
SEI	solid electrolyte interphase
SHM	structural health management; system health monitoring
SIA	Semiconductor Industry Association
SIR	sampling importance resampling
SIS	sequential important sampling
SIV	stress-induced voiding

SLI	starting-lighting-ignition
SLOC	source lines of code
SLPP	supervised locality preserving projection
SMART	self-monitoring analysis and reporting technology
SMOTE	synthetic minority oversampling technique
SOA	service-oriented architecture
SOC	state of charge
SOH	state of health
SOM	self-organizing map
SPD	spectral power distribution
SPRT	sequential probability ratio test
SRB	solid rocket booster
SRMS	shuttle remote manipulator system
SRU	shop-replaceable unit
SSE	Scottish and Southern Energy
SVM	support vector machine
SVR	support vector regression
TC	type certificate
TDDB	time-dependent dielectric breakdown
TDR	time domain reflectometry
TEF	transient earth fault
TEG	thermoelectric generator
THB	temperature/humidity/bias
TMS	transmitter management subsystem
TN	true negative
TNI	trouble not identified
TP	true positive
TPR	true positive rate
TSM	troubleshooting manual
TSMD	time-stress measurement device
TSV	through-silicon via
TTF	time-to-failure
UAP	uncertainty adjusted prognostics
UAV	unmanned aerial vehicle
UBL	usage-based lifing
UE	user equipment
UER	unscheduled engine removal
uHAST	unbiased highly accelerated stress test
UKF	unscented Kalman filter
USABC	US Advanced Battery Consortium
USB	universal serial bus
USPTO	US Patent and Trademark Office
UT	unscented transform
UV	ultra-violet
V&V	verification and validation
V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle

VBA	Visual Basic for Applications
VCE	collector–emittor voltage
VFSG	variable frequency starter generator
VLSI	very large scale integrated
VSWR	voltage standing wave ratio
WSN	wireless sensor network
XLPE	crosslinked polyethylene
XML	extensible markup language
ZDS	zero defect sampling
ZVEI	Zentralverband Elektrotechnik und Elektronikindustrie

1

Introduction to PHM

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As a result of intense global competition, companies are considering novel approaches to enhance the operational efficiency of their products. For some products, high in-service reliability can be a means to ensure customer satisfaction. For other products, increased warranties, or at least reduced warranty costs, and a reduction in liability due to product failures, are incentives for manufacturers to improve field reliability and operational availability.[1]

Electronics are integral to the functionality of most systems today, and their reliability is often critical for system reliability [1]. Interest has been growing in monitoring the ongoing health of electronics products, whether they be components, systems, or systems-of-systems, to provide advance warning of failure and assist in administration and logistics. Here, health is defined as the extent of degradation or deviation from an expected normal condition. Prognostics is the prediction of the future state of health based on current and historical health conditions [2]. This chapter provides a basic understanding of prognostics and health monitoring of products and the techniques being developed to enable prognostics for electronic products.

1.1 Reliability and Prognostics

Reliability is the ability of a product to perform as intended (i.e. without failure and within specified performance limits) for a specified time, in its life-cycle environment [3]. Traditional reliability prediction methods for electronic products include Mil-HDBK-217 [4], 217-PLUS, Telcordia [5], PRISM [6], and FIDES [7]. These methods rely on the collection of failure data and generally assume the components of the system have failure rates (most often assumed to be constant) that can be modified by independent "modifiers" to account for various quality, operating, and environmental conditions. There are numerous well-documented concerns with this type of modeling approach [8–11]. The general consensus is that these handbooks should never be

1 Operational availability is defined as the degree (expressed as a decimal between 0 and 1, or the percentage equivalent) to which a piece of equipment or system can be expected to work properly when required. Operational availability is often calculated by dividing uptime by the sum of uptime and downtime.

Prognostics and Health Management of Electronics: Fundamentals, Machine Learning, and the Internet of Things, First Edition. Edited by Michael G. Pecht and Myeongsu Kang.

used, because they are inaccurate for predicting actual field failures and provide highly misleading predictions, which can result in poor designs and logistics decisions [9, 12]. In particular, a recent National Academy of Science study recommended that the use of Mil-HDBK-217 and its progeny be considered as discredited for being invalid and inaccurate: they should be replaced with physics-of-failure (PoF) methods and with estimates based on validated models [13].

The traditional handbook method for the reliability prediction of electronics started with Mil-HDBK-217A, published in 1965. In this handbook, there was only a single point failure rate for all monolithic integrated circuits (ICs), regardless of the stresses, the materials, or the architecture. Mil-HDBK-217B was published in 1973, with the RCA/Boeing models simplified by the US Air Force to follow a statistical exponential (constant failure rate) distribution. Since then, all the updates were mostly "band-aids" for a modeling approach that was proven to be flawed [14]. In 1987–1990, the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland was awarded a contract to update Mil-HDBK-217. It was concluded that this handbook should be canceled and the use of this type of modeling approach discouraged.

In 1998, the Institute of Electrical and Electronics Engineers (IEEE) 1413 standard, *IEEE Standard Methodology for Reliability Prediction and Assessment for Electronic Systems and Equipment*, was approved to provide guidance on the appropriate elements of a reliability prediction [15]. A companion guidebook, *IEEE 1413.1, IEEE Guide for Selecting and Using Reliability Predictions Based on IEEE 1413*, provided information and an assessment of the common methods of reliability prediction for a given application [16]. It is shown that the Mil-HDBK-217 is flawed. There is also discussion of the advantage of reliability prediction methods that use stress and damage PoF techniques.

The PoF approach and design-for-reliability (DfR) methods have been developed by CALCE [17] with the support of industry, government, and other universities. PoF is an approach that utilizes knowledge of a product's life-cycle loading and failure mechanisms to perform reliability modeling, design, and assessment. The approach is based on the identification of potential failure modes, failure mechanisms, and failure sites for the product as a function of its life-cycle loading conditions. The stress at each failure site is obtained as a function of both the loading conditions and the product geometry and material properties. Damage models are then used to determine fault generation and propagation.

PoF is one approach to prognostics, but not the only approach. Prognostics and systems health management (PHM) is a multifaceted discipline for the assessment of product degradation and reliability. The purpose is to protect the integrity of the product and avoid unanticipated operational problems leading to mission performance deficiencies, degradation, and adverse effects on mission safety. More specifically, prognostics is the process of predicting a system's remaining useful life (RUL) by estimating the progression of a fault given the current degree of degradation, the load history, and the anticipated future operational and environmental conditions. Health management is the process of decision-making and implementing actions based on the estimate of the state of health derived from health monitoring and expected future use of the product.

In general, PHM consists of sensing, anomaly detection, diagnostics, prognostics, and decision support, as shown in Figure 1.1. Sensing is to collect a history of time-dependent operation of a product, the degradation of materials, and/or the environmental loads on the components of a product or the total product.

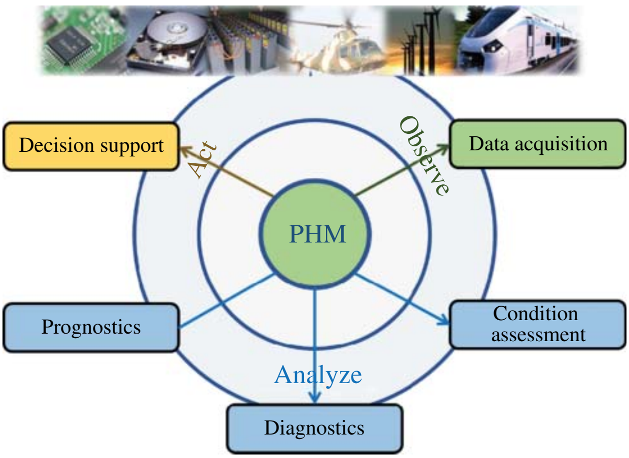

Figure 1.1 Framework for prognostics and health management.

The primary purpose of anomaly detection is to identify strange or unusual or unexpected (anomalous) behavior of the product by identifying deviations from nominally healthy behavior. The results from anomaly detection can provide advanced warnings of failure, often referred to as failure precursors. Note that anomalies do not necessarily indicate a failure because changes in operating and environmental conditions can influence sensor data to show anomalous behavior. However, even this type of anomaly information is valuable to product health management, because it can indicate an unexpected use.

Diagnostics enables the extraction of fault-related information, such as failure modes, failure mechanisms, quantity of damage, and so forth, from sensor data caused by anomalies in the health of the product. This is a key piece of information that feeds into maintenance planning and logistics.

Prognostics refers to predicting a product's RUL within appropriate confidence intervals, which often requires additional information not traditionally provided by sensors, such as maintenance history, past and future operating profiles, and environmental factors. Based on predictions, the goal is to inform decision-makers of potential cost avoidance activities, and to ensure safe operation. That is, the aspects of PHM are to effect appropriate decision-making; to prevent catastrophic system failures; to increase system availability by reducing downtime; to expend maintenance cycles; to execute timely repair actions; to lower life-cycle costs by reductions in inspection and repair; and to improve system qualification, design, and logistical support.

1.2 PHM for Electronics

Most products contain some amount of electronic content, generally needed for functionality and performance. With the increase in the Internet of Things (IoT) it is being seen that the electronics content is in fact rapidly increasing. If one can assess the extent of deviation or degradation from an expected normal operating condition for electronics, this information can be used to meet several powerful goals, which include

(i) providing advanced warning of failures; (ii) minimizing unscheduled maintenance, extending maintenance cycles, and maintaining effectiveness through timely repair actions; (iii) reducing the life-cycle cost of equipment by decreasing inspection costs, downtime, and inventory; and (iv) improving qualification and assisting in the design and logistical support of fielded and future systems [2]. In other words, since electronics are playing an increasingly significant role in providing operational capabilities for today's products, prognostic techniques have become highly desirable.

Some of the first efforts in diagnostic health monitoring of electronics involved the use of built-in test (BIT), defined as an onboard hardware–software diagnostic means to identify and locate faults. A BIT can consist of error detection and correction circuits, totally self-checking circuits, and self-verification circuits [2]. There are two types of BIT concepts employed in electronic systems: interruptive built-in test (I-BIT) and continuous built-in test (C-BIT). The concept behind I-BIT is that normal equipment operation is suspended during BIT operation, whereas for C-BIT the equipment is monitored continuously and automatically without affecting normal operation.

Several studies [18, 19] conducted on the use of BIT for fault identification and diagnostics showed that BIT can be prone to false alarms and can result in unnecessary costly replacement, requalification, delayed shipping, and loss of system availability. BIT concepts are still being developed to reduce the occurrence of spurious failure indications. However, there is also reason to believe that many of the failures did occur, but were intermittent in nature [20]. Furthermore, BIT has generally not been designed to provide prognostics or RUL due to accumulated damage or progression of faults. Rather, it has served primarily as a diagnostic tool.

PHM has also emerged as one of the key enablers for achieving efficient system-level maintenance and lowering life-cycle costs in military systems. In November 2002, the US Deputy Under Secretary of Defense for Logistics and Material Readiness released a policy called condition-based maintenance plus (CBM+). CBM+ represents an effort to shift unscheduled corrective equipment maintenance of new and legacy systems to preventive and predictive approaches that schedule maintenance based upon the evidence of need. A 2005 survey of 11 CBM programs highlighted "electronics prognostics" as one of the most needed maintenance-related features or applications without regard for cost [21], a view also shared by the avionics industry [22]. Department of Defense 5000.2 policy document on defense acquisition stated that "program managers shall optimize operational readiness through affordable, integrated, embedded diagnostics and prognostics, embedded training and testing, serialized item management, automatic identification technology, and iterative technology refreshment" [20]. Thus, a prognostics capability has become a requirement for any system sold to the US Department of Defense.

PHM has also emerged as a high-priority issue in space applications. NASA's Ames Research Center (ARC) in California is conducting research in the field of integrated systems health management (ISHM). ARC is involved in design of health management systems, selection and optimization of sensors, in-situ monitoring, data analysis, prognostics, and diagnostics. The prognostics center for excellence at ARC develops algorithms to predict the remaining life of NASA's systems and subsystems. ARC's prognostics projects over the years have included power semiconductor devices (investigation of the effects of aging on power semiconductor components, identification of failure precursors to build a PoF model, and development of algorithms for end-of-life prediction), batteries (algorithms for batteries prognosis), flight actuators

(PoF modeling and development of algorithms for estimation of remaining life), solid rocket motor failure prediction, and aircraft wiring health management.

In addition to in-service reliability assessment and maintenance, health monitoring can also be used effectively to support product take-back and end-of-life decisions. Product take-back indicates the responsibility of manufacturers for their products over the entire life-cycle, including disposal. The motivation driving product take-back is the concept of extended producer responsibility (EPR) for post-consumer electronic waste [23]. The objective of EPR is to make manufacturers and distributors financially responsible for their products when they are no longer needed.

End-of-life product recovery strategies include repair, refurbishment, remanufacturing, re-use of components, material recycling, and disposal. One of the challenges in end-of-life decision-making is to determine whether product lines can be extended, whether components can be re-used, and what subset should be disposed of in order to minimize system costs and reliability concerns [24]. Several interdependent issues must be considered concurrently to properly determine the optimum component re-use ratio, including assembly/disassembly costs and any defects introduced by the process, product degradation incurred in the original life-cycle, and the waste stream associated with the life-cycle. Among these factors, the estimate of the degradation of the product in its original life-cycle could be the most uncertain input to end-of-life decisions, but could be carried out using health monitoring, with knowledge of the entire history of the product.

Scheidt and Zong [25] proposed the development of special electrical ports, referred to as green ports, to retrieve product usage data that could assist in the recycling and re-use of electronic products. Klausner et al. [26, 27] proposed the use of an integrated electronic data log (EDL) for recording parameters indicative of product degradation. The EDL was implemented on electric motors to increase the re-use of motors. In another study, domestic appliances were monitored for collecting usage data by means of electronic units fitted on the appliances [28]. This work introduced the life-cycle data acquisition unit, which can be used for data collection and for diagnostics and servicing. Middendorf et al. [29] suggested developing life information modules to record the cycle conditions of products for reliability assessment, product refurbishing, and re-use.

Designers often establish the usable life of products and warranties based on extrapolating accelerated test results to assumed usage rates and life-cycle conditions. These assumptions may be based on worst-case scenarios of various parameters composing the end-user environment. In principle, if the assumed conditions and actual use conditions are the same, the product should be reliable for the designed lifetime, as shown in Figure 1.2a. However, this is rarely true, and usage and environmental conditions could vary significantly from those assumed (see Figure 1.2b). To address the actual life-cycle conditions, products can be equipped with life consumption monitors (LCMs) for in-situ assessment of remaining life. Thus, even if the product is used at a higher usage rate and in harsh conditions, it can still avoid unscheduled maintenance and catastrophic failure, maintain safety, and ultimately save cost. Or if the product is used in a more benign manner, its life can be extended (see Figure 1.2c).

One of the vital inputs in making end-of-life decisions is the estimate of degradation and the remaining life of the product. Figure 1.2c illustrates a scenario in which a working product is returned at the end of its designed life. Using the health monitors installed within the product, the reusable life can be assessed, without having to disassemble the

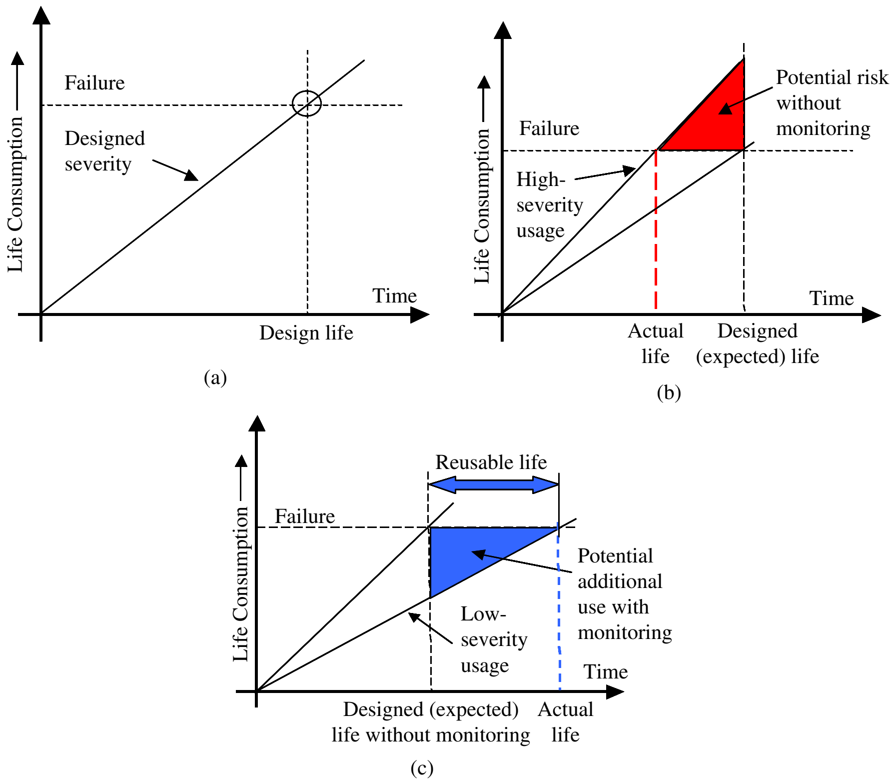

Figure 1.2 Application of health monitoring for product re-use. (a) Usage as per design, (b) More severe usage than intended design, and (c) Less severe usage than intended design.

product. Ultimately, depending on other factors including cost of the product, demand for spares, and yield in assembly and disassembly, the manufacturer can choose to re-use or dispose.

1.3 PHM Approaches

To enable PHM, the PoF-, canary-, data-driven-, and fusion-based approaches have been studied. In this section, each of these approaches is explained. Further, various applications using these approaches are presented.

1.3.1 PoF-Based Approach

The general PHM methodology is shown in Figure 1.3. The first step involves a virtual life assessment, where design data, expected life-cycle conditions, failure modes, mechanisms, and effects analysis (FMMEA) [30], and PoF models are the inputs to obtain a reliability (virtual life) assessment. Note that PoF models are sometimes not available in new designs where an up-front design for reliability was not implemented because they tend to be failure mechanism-specific. Based on the virtual life assessment, it is

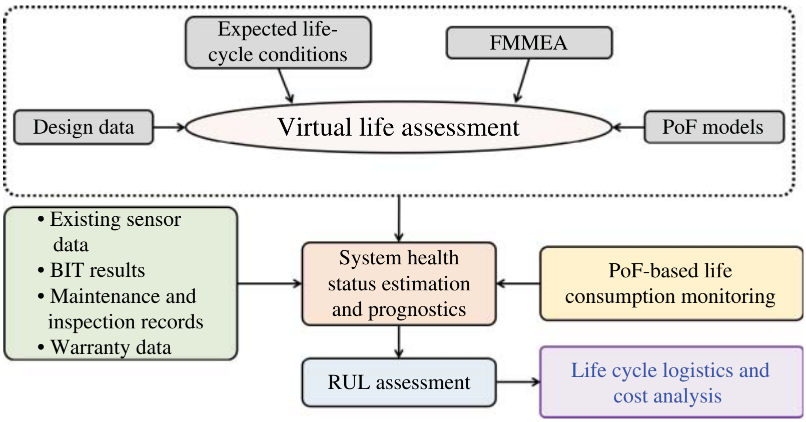

Figure 1.3 CALCE PHM methodology.

possible to prioritize the critical failure modes and mechanisms. Further, the existing sensor data, BIT results, maintenance and inspection records, and warranty data can be used for the identification of possible failure conditions. Based on this information, the monitoring parameters and sensor locations for PHM can be determined.

Based on the collected operational and environmental data, the product's health status can be assessed. Damage estimates can also be calculated from the PoF models to obtain the remaining life. Then PHM information can be used for maintenance forecasting and decisions that minimize life-cycle costs or maximize availability. The main advantage of a PoF-based prognostics approach is the ability to incorporate an engineering-based understanding of the product into PHM by using knowledge of the materials and geometries of a system, as well as the load conditions (e.g. thermal, mechanical, electrical, chemical) over the life-cycle.

1.3.1.1 Failure Modes, Mechanisms, and Effects Analysis (FMMEA)

A PoF approach uses knowledge of how things degrade and fail. This knowledge is based on physical laws linked with a mathematical model [31]. An understanding of the process by which physical, electrical, chemical, and mechanical stresses act on materials to induce failure is required. As shown in Figure 1.4, FMMEA is the one of the first steps for PoF-based prognostics, with the goal of identifying the critical failure mechanisms and failure sites for a given product. Then, the following subsequent steps involve (i) monitoring the life-cycle loads that may lead to performance or physical degradation and the associated system responses; (ii) feature extraction from variables that change in response to deterioration associated with the failure mechanisms identified via FMMEA; (iii) damage assessment and RUL calculation using PoF models of the failure mechanisms; and (iv) uncertainty estimation and time-to-failure (TTF) prediction as a distribution.

FMMEA provides a list of potential failure modes, mechanisms, and the corresponding models of system (see Table 1.1). FMMEA assigns scores to each potential failure mode and ranks them to identify the critical failure modes according to the occurrence, severity, and detectability.

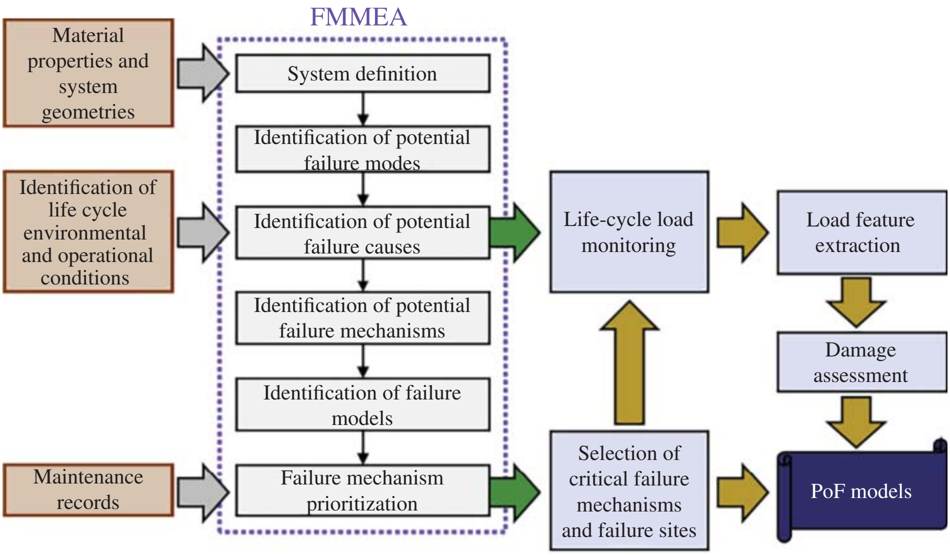

Figure 1.4 PoF-based prognostics approach [32].

Table 1.1 Examples of failure mechanisms, loads, and failure models in electronics via FMMEA, where *T*, *H*, *V*, *M*, *J*, and *S* indicate temperature, humidity, voltage, moisture, current density, and stress, respectively, and Δ and ∇ mean cyclic range and gradient.

Failure sites	Failure mechanisms	Loads	Failure models
Die attach, wirebond, solder leads, bond pads, traces, vias, interfaces	Fatigue	ΔT, T_{mean}, dT/dt, dwell time, ΔH, ΔV	Nonlinear power law (Coffin–Manson)
Metallization	Corrosion	M, ΔV, T	Eyring (Howard)
Metallization	Electromigration	T, J	Eyring (Black)
Between metallization	Conductive filament formation	M, ∇V	Power law (Rudra)
Stress-driven diffusion voiding	Metal traces	S, T	Eyring (Okabayashi)
Time-dependent dielectric breakdown	Dielectric layers	V, T	Arrhenius (Fowler–Nordheim)

1.3.1.2 Life-Cycle Load Monitoring

The life-cycle profile of a product consists of manufacturing, storage, handling, and operating and non-operating conditions. The life-cycle loads (see Table 1.2), both individually or in various combinations, may lead to performance or physical degradation of the product and reduce its service life [33]. The extent and rate of product degradation depend upon the magnitude and duration of exposure (usage rate, frequency, and severity) to such loads. If one can measure these loads in situ, the load profiles can be

Table 1.2 Examples of life-cycle loads.

Load	Load conditions
Thermal	Steady-state temperature, temperature ranges, temperature cycles, temperature gradients, ramp rates, heat dissipation
Mechanical	Pressure magnitude, pressure gradient, vibration, shock load, acoustic level, strain, stress
Chemical	Aggressive versus inert environment, humidity level, contamination, ozone, pollution, fuel spills
Physical	Radiation, electromagnetic interference, altitude
Electrical	Current, voltage, power, resistance

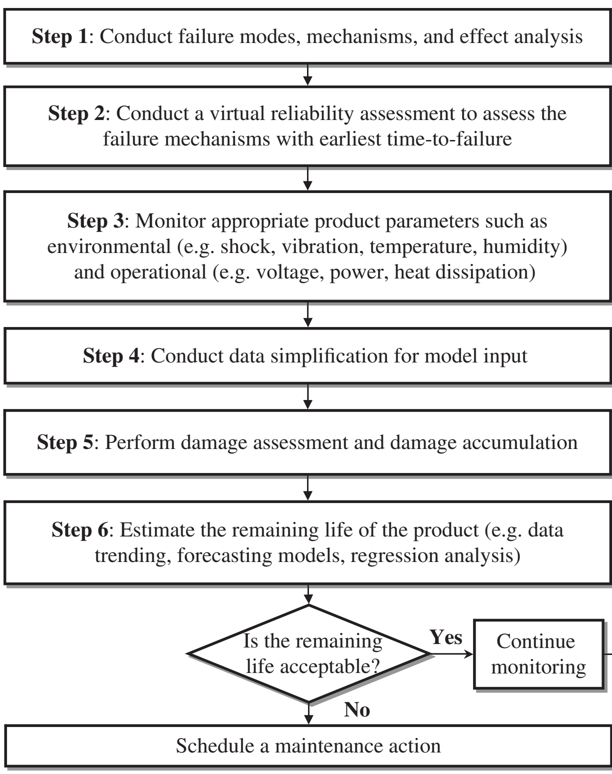

Figure 1.5 CALCE life consumption monitoring methodology.

used in conjunction with damage models to assess the degradation due to cumulative load exposures.

The assessment of the impact of life-cycle usage and environmental loads on electronic structures and components was studied by Ramakrishnan and Pecht [33]. This study introduced the LCM methodology (Figure 1.5), which combined in-situ measured loads with physics-based stress and damage models to assess remaining product life.

Mathew et al. [34] applied the LCM methodology to conduct a prognostic remaining life assessment of circuit cards inside a space shuttle solid rocket booster (SRB). Vibration-time history, recorded on the SRB from the prelaunch stage to splashdown, was used in conjunction with physics-based models to assess damage. Using the entire life-cycle loading profile of the SRBs, the remaining life of the components and structures on the circuit cards were predicted. It was determined that an electrical failure was not expected within another 40 missions. However, vibration and shock analysis exposed an unexpected failure due to a broken aluminum bracket mounted on the circuit card. Damage accumulation analysis determined that the aluminum brackets had lost significant life due to shock loading.

Shetty et al. [35] applied the LCM methodology to conduct a prognostic remaining-life assessment of the end-effector electronics unit (EEEU) inside the robotic arm of the space shuttle remote manipulator system (SRMS). A life-cycle loading profile of thermal and vibrational loads was developed for the EEEU boards. Damage assessment was conducted using physics-based mechanical and thermomechanical damage models. A prognostic estimate using a combination of damage models, inspection, and accelerated testing showed that there was little degradation in the electronics, and they could be expected to last another 20 years.

Gu et al. [36] developed a methodology for monitoring, recording, and analyzing the life-cycle vibration loads for remaining-life prognostics of electronics. The responses of printed circuit boards (PCBs) to vibration loading in terms of bending curvature were monitored using strain gauges. The interconnect strain values were then calculated from the measured PCB response and used in a vibration failure fatigue model for damage assessment. Damage estimates were accumulated using Miner's rule after every mission and then used to predict the life consumed and remaining life. The methodology was demonstrated for remaining-life prognostics of a PCB assembly. The results were also verified by checking the resistance data.

In case studies [33, 37], an electronic component board assembly was placed under the hood of an automobile and subjected to normal driving conditions. Temperature and vibrations were measured in situ in the application environment. Using the monitored environmental data, stress and damage models were developed and used to estimate consumed life. Figure 1.6 shows estimates obtained using similarity analysis and the actual measured life. Only LCM accounted for this unforeseen event because the operating environment was being monitored in situ.

Vichare and Pecht [2] outlined generic strategies for in-situ load monitoring, including selecting appropriate parameters to monitor, and designing an effective monitoring plan. Methods were presented for processing the raw sensor data during in-situ monitoring to reduce the memory requirements and power consumption of the monitoring device. Approaches were also presented for embedding intelligent front-end data processing capabilities in monitoring systems to enable data reduction and simplification (without sacrificing relevant load information) prior to input in damage models for health assessment and prognostics.

1.3.1.3 Data Reduction and Load Feature Extraction

To reduce on-board storage space, power consumption, and uninterrupted data collection over longer durations, Vichare et al. [38] suggested embedding data reduction and load parameter extraction algorithms into sensor modules. As shown in Figure 1.7,

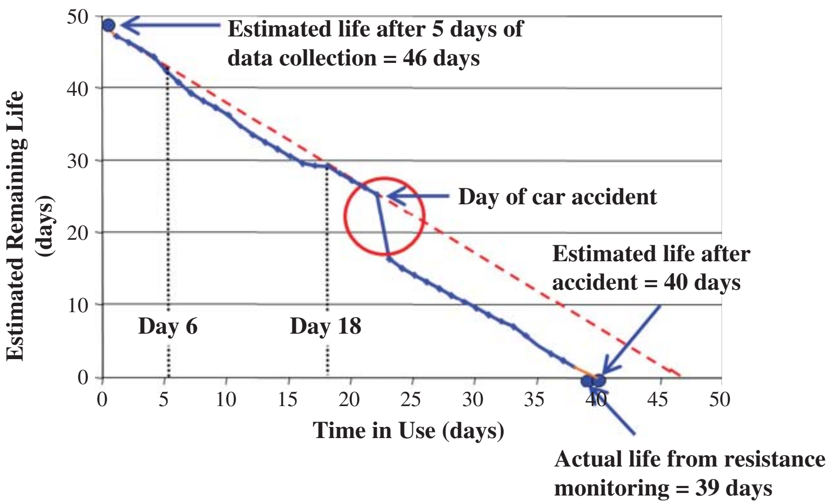

Figure 1.6 Remaining life estimation of test board.

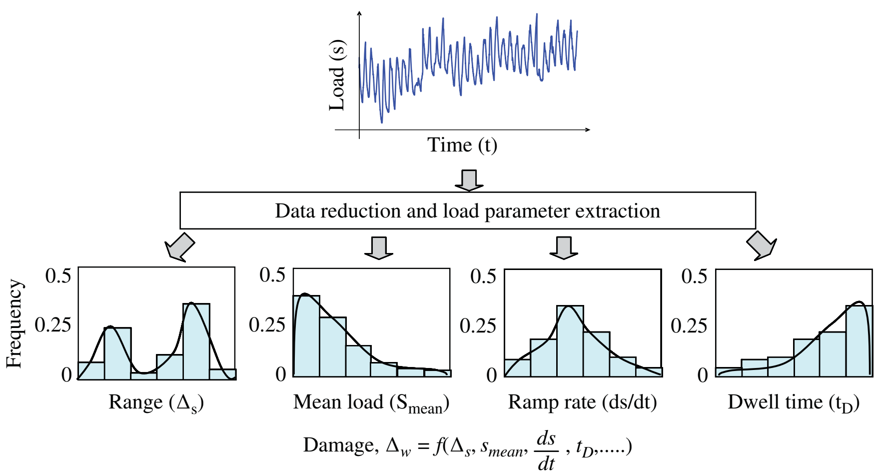

Figure 1.7 Load feature extraction.

a time-load signal can be monitored in situ using sensors and further processed to extract cyclic range (Δs), cyclic mean load (s_{mean}), rate of change of load (ds/dt), and dwell time (t_D) using embedded load extraction algorithms. The extracted load parameters can be stored in appropriately binned histograms to achieve further data reduction. After the binned data are downloaded, they can be used to estimate the distributions of the load parameters. This type of output can be input to fatigue damage accumulation models for remaining life prediction. Embedding the data reduction and load parameter extraction algorithms into the sensor modules can lead to a reduction in on-board storage space, lower power consumption, and uninterrupted data collection over longer durations.

Efforts to monitor life-cycle load data on avionics modules can be found in time-stress measurement device (TSMD) studies. Over the years TSMD designs have been upgraded using advanced sensors, and miniaturized TSMDs are being developed with advances in microprocessor and nonvolatile memory technologies [39].

Searls et al. [40] undertook in-situ temperature measurements in both notebook and desktop computers used in different parts of the world. In terms of the commercial applications of this approach, IBM has installed temperature sensors on hard drives [41] to mitigate risks due to severe temperature conditions, such as thermal tilt of the disk stack and actuator arm, off-track writing, data corruptions on adjacent cylinders, and outgassing of lubricants on the spindle motor. A sensor is controlled using a dedicated algorithm to generate errors and control fan speeds.

Strategies for efficient in-situ health monitoring of notebook computers were provided by Vichare et al. [42]. In this study, the authors monitored and statistically analyzed the temperatures inside a notebook computer, including those experienced during usage, storage, and transportation, and discussed the need to collect such data both to improve the thermal design of the product and to monitor prognostic health. The temperature data were processed using an ordered overall range (OOR) to convert an irregular time–temperature history into peaks and valleys and to remove noise due to small cycles and sensor variations. A three-parameter rainflow algorithm was then used to process the OOR results to extract full and half cycles with cyclic range, mean, and ramp rates. The effects of power cycles, usage history, central processing unit (CPU) computing resources usage, and external thermal environment on peak transient thermal loads were characterized.

1.3.1.4 Data Assessment and Remaining Life Calculation

In 2001, the European Union funded a four-year project, "Environmental Life-Cycle Information Management and Acquisition" (ELIMA), which aimed to develop ways to manage the life-cycles of products [43]. The objective of this work was to predict the remaining life of parts removed from products, based on dynamic data, such as operation time, temperature, and power consumption. As a case study, the member companies monitored the application conditions of a game console and a household refrigerator. The work concluded that, in general, it was essential to consider the environments associated with all life intervals of the equipment. These included not only the operational and maintenance environments but also the preoperational environments, when stresses may be imposed on the parts during manufacturing, assembly, inspection, testing, shipping, and installation. Such stresses are often overlooked but can have a significant impact on the eventual reliability of equipment.

Skormin et al. [44] developed a data-mining model for failure prognostics of avionics units. The model provided a means of clustering data on parameters measured during operation, such as vibration, temperature, power supply, functional overload, and air pressure. These parameters are monitored in situ on the flight using TSMDs. Unlike the physics-based assessments made by Ramakrishnan and Pecht [33], the data-mining model relies on statistical data of exposures to environmental factors and operational conditions.

Tuchband and Pecht [45] presented the use of prognostics for military line replaceable units (LRUs) based on their life-cycle loads. The study was part of an effort funded by the Office of the Secretary of Defense to develop an interactive supply chain system for the US military. The objective was to integrate prognostics, wireless communication, and databases through a web portal to enable cost-effective maintenance and replacement of electronics. The study showed that prognostics-based maintenance scheduling could be implemented into military electronic systems. The approach involves an integration of embedded sensors on the LRU, wireless communication for data transmission, a PoF-based algorithm for data simplification and damage estimation, and a method for uploading this information to the Internet. Finally, the use of prognostics for electronic military systems enabled failure avoidance, high availability, and reduction of life-cycle costs.

1.3.1.5 Uncertainty Implementation and Assessment

Although PoF models are used to compute the RUL, the introduction of uncertainties into the calculation is necessary to assess their impact on the remaining life distribution to make risk-informed decisions. That is, remaining life prediction can be represented by a failure probability by considering uncertainties in prediction.

Gu et al. [46] implemented the uncertainty analysis of prognostics for electronics under vibration loading. Gu identified the uncertainty sources and categorized them into four different types: measurement uncertainty, parameter uncertainty, failure criteria uncertainty, and future usage uncertainty (see Figure 1.8). Gu et al. [46] utilized a sensitivity analysis to identify the dominant input variables that influence the model output. With information of input parameter variable distributions, a Monte Carlo simulation was used to provide a distribution of accumulated damage. The remaining life was then predicted with confidence intervals and confidence limits (CLs). A case study was also presented for an electronic board under vibration loading and a step-by-step demonstration of the uncertainty analysis implementation. The results showed that the experimentally measured failure time was within the bounds of the uncertainty analysis prediction.

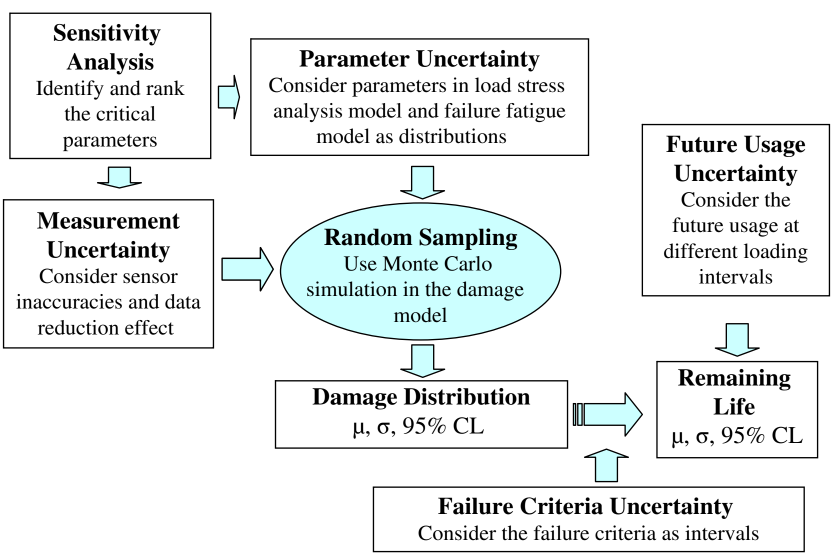

Figure 1.8 Uncertainty implementation for prognostics.

1.3.2 Canaries

As previously stated, PoF is one approach to the implementation of prognostics that utilizes knowledge of a product's life-cycle loading conditions, geometry, material properties, and failure mechanisms to estimate its RUL. However, due to the inherent uncertainties in operating environment factors (e.g. temperature, humidity, vibration, corrosive substances), the lifetime of an electronic product in field conditions might be substantially different from the lifetime measured under the controlled and specified conditions in laboratories.

The use of canary devices is one approach to taking the uncertainties in the operating environment of electronics into account. An IC or PCB in an electronic device can be equipped with a component that experiences the expected and unexpected loads encountered during the operating life of the equipment, but fails earlier than the target system. Such a component is called a canary. More specifically, a PoF-based canary approach takes into account geometry, material properties, and failure mechanisms, in addition to the real operating environments in which the target component operates, to provide an advance warning of failure of the target components.

Fuses and circuit breakers are examples of elements used in electronic products to sense excessive current drain and to disconnect power. Fuses within circuits safeguard parts against excessive voltage transients or excessive power dissipation, and protect power supplies from short-circuiting. For example, thermostats can be used to sense critical temperature limiting conditions and to shut down the product (or part of a system), until the temperature returns to normal. In some products, self-checking circuitry can be incorporated to sense abnormal conditions and to make adjustments to restore normal conditions or to activate switching means to compensate for a malfunction [47].

Mishra and Pecht [48] studied the applicability of semiconductor-level health monitors by using pre-calibrated cells (circuits) manufactured (concurrently with the device circuitry) and located on the same semiconductor chip. The prognostics cell approach, known as Sentinel Semiconductor™ technology, was commercialized to provide an early warning sentinel for upcoming device failures [49]. The prognostic cells were available for 0.35 μm, 0.25 μm, and 0.18 μm complementary metal-oxide-semiconductor (CMOS) processes; the power consumption was approximately 600 μW. The cell size was typically 800 μm^2 at the 0.25 μm process size. The loads that contribute to degradation of the circuit include voltage, current, temperature, humidity, and radiation. Currently, smaller prognostic cells are available for more state-of-the-art semiconductors, for failure mechanisms including electrostatic discharge (ESD), hot carrier, metal migration, dielectric breakdown, and radiation effects.

The time-to-failure of prognostic canaries can be precalibrated with respect to the time-to-failure of the product (the chip circuitry). There are two major designs to accomplish the early warning feature. The first is where the canary architecture is substantially the same as the chip circuitry, but the loading is accelerated with respect to the chip circuitry. The second is where the loads are the same as those applied to the actual circuitry, but the canary architecture is designed to fail sooner than the chip circuitry, by causing more stress on the canary. There can also be a combination of the two.

If the architecture and the operational loads (stresses) are the same, the damage rate is expected to be the same for both circuits. Scaling (accelerated failure) can be achieved by controlled increase of the stresses (e.g. current density) inside the canaries.

For example, with the same amount of current (load) passing through both circuits, if the cross-sectional area of the current-carrying paths in the canary is decreased, a higher current density (stress condition) will be achieved. Higher current density leads to higher internal (joule) heating, causing greater stress on the canaries. When a current of higher density passes through the canaries, they are expected (based on PoF models) to fail faster than the actual circuit [48].

Goodman et al. [50] used a prognostic canary to monitor time-dependent dielectric breakdown (TDDB) of the metal-oxide-semiconductor field-effect transistor (MOSFET) on the ICs. Acceleration of the breakdown of an oxide was achieved by applying a voltage higher than the supply voltage to increase the electric field across the oxide. When the prognostics canary failed, a certain fraction of the circuit lifetime was consumed. The fraction of consumed circuit life was dependent on the amount of overvoltage applied, and could be estimated from the known PoF failure distribution models.

The extension of this approach to board-level failures was proposed by Anderson and Wilcoxon [51], who created canary components (located on the same PCB) that include the same mechanisms that lead to failure in actual components. Two prospective failure mechanisms were identified: (i) low cycle fatigue of solder joints, assessed by monitoring solder joints on and within the canary package, and (ii) corrosion monitoring, using circuits that are susceptible to corrosion. The environmental degradation of these canaries was assessed using accelerated testing, and degradation levels were calibrated and correlated to actual failure levels of the main system. The corrosion test device included electrical circuitry susceptible to various corrosion-induced mechanisms. Impedance spectroscopy was proposed for identifying changes in the circuits by measuring the magnitude and phase angle of impedance as a function of frequency. The change in impedance characteristics can be correlated to indicate specific degradation mechanisms.

Mathew et al. [52] presented an approach of using a surface mount resistor with reduced solder attachment as a canary device for predicting failure of a ball grid array (BGA) package. More specifically, the authors used 2015 and 1210 resistors with x% solder pad area, respectively, to predict the solder fatigue failure of 192 I/O ChipArray® ball grid arrays (CABGAs), and explored the impact of the size of the resistor and the solder pad area. They found that the 2512 resistor with 20% pad area provided a longer prognostic distance than the 1210 resistor with 20% pad area. Further, the prognostic distance obtained from the 2512 resistor with 50% solder pad area is shorter than the 2512 resistor with 20% pad area. Accordingly, they concluded that the prognostic distance for the 192 I/O CABGA could vary by the size of the resistor and the solder pad area. In 2015, Mathew et al. [53] developed a generic methodology to implement canary devices, which is effective for tackling practical issues including the determination of the number of canary devices required and the confidence in the prediction for a certain number of canaries. Likewise, the authors presented a failure prediction scheme to estimate system failure based on the failure of the canary device in the field.

Chauhan et al. [54] introduced a PoF-based canary approach for early identification of solder interconnect failures, where the developed canary device was composed of a resistance path formed by a near-zero-ohm ceramic chip resistor soldered to pads designed to produce failure earlier than the target resistors (i.e. standard pad resistors). Further, the authors controlled the TTF of the canary device by adjusting the printed wiring board pad dimensions, hence, the solder interconnect area. Likewise, the authors employed the Engelmaier model to provide TTF estimates for the canary and target structures, which is a PoF-based model for solder interconnect life estimation under thermal cycling.

There remain unanswered questions with the use of canaries for PHM. For example, if a canary monitoring a circuit is replaced, what is the impact when the product is re-energized? What protective architectures are appropriate for post-repair operations? What maintenance guidance must be documented and followed when fail-safe protective architectures have or have not been included? The canary approach is also difficult to implement in legacy systems because it may require requalification of the entire system with the canary module. Also, the integration of fuses and canaries with the host electronic system could be an issue with respect to real estate on semiconductors and boards. Finally, the company must ensure that the additional cost of implementing PHM can be recovered through increased operational and maintenance efficiencies.

1.3.3 Data-Driven Approach

Data-driven approaches use data analytics and machine learning to determine anomalies and make predictions about the reliability of electronic devices, systems, and products based on internal and/or external covariates (also called endogenous and exogenous covariates). Internal covariates (e.g. temperature, vibration) are measured by sensors on the asset and are only present when the asset is operating. External covariates (e.g. weather data) are present whether or not the asset is operating [55]. The data-driven approach analyzes asset performance data based on a training database of internal and/or external covariates.

1.3.3.1 Monitoring and Reasoning of Failure Precursors

A failure precursor is a data event or trend that signifies impending failure. A precursor indication is usually a change in a measurable variable that can be associated with subsequent failure. For example, a shift in the output voltage of a power supply might suggest impending failure due to a damaged feedback regulator and opto-isolator circuitry. Failures can then be predicted by using causal relationships between measured variables that can be correlated with subsequent failure and for PoF.

A first step in failure precursor PHM is to select the life-cycle parameters to be monitored. Parameters can be identified based on factors that are crucial for safety, that are likely to cause catastrophic failures, that are essential for mission completeness, or that can result in long downtimes. Selection can also be based on knowledge of the critical parameters established by experience, field failure data on similar products, and qualification testing. More systematic methods, such as FMMEA [30], can also be used to determine parameters that need to be monitored. Pecht et al. [56] proposed several measurable parameters that can be used as failure precursors for electronic products, including switching power supplies, cables and connectors, CMOS ICs, and voltage-controlled high-frequency oscillators (see Table 1.3).

In general, to implement a precursor reasoning-based PHM system, it is necessary to identify the precursor variables for monitoring and then develop a reasoning algorithm to correlate the change in the precursor variable with the impending failure. This characterization is typically performed by measuring the precursor variable under an expected or accelerated usage profile. Depending on the characterization, a model is

Table 1.3 Potential failure precursors for electronics [56].

Electronic subsystem	Failure precursor
Switching power supply	• Direct-current (DC) output (voltage and current levels) • Ripple • Pulse width duty cycle • Efficiency • Feedback (voltage and current levels) • Leakage current • Radio frequency (RF) noise
Cables and connectors	• Impedance changes • Physical damage • High-energy dielectric breakdown
CMOS IC	• Supply leakage current • Supply current variation • Operating signature • Current noise • Logic-level variations
Voltage-controlled oscillator	• Output frequency • Power loss • Efficiency • Phase distortion • Noise
Field effect transistor	• Gate leakage current/resistance • Drain-source leakage current/resistance
Ceramic chip capacitor	• Leakage current/resistance • Dissipation factor • RF noise
General-purpose diode	• Reverse leakage current • Forward voltage drops • Thermal resistance • Power dissipation • RF noise
Electrolytic capacitor	• Leakage current/resistance • Dissipation factor • RF noise
RF power amplifier	• Voltage standing wave ratio (VSWR) • Power dissipation • Leakage current

developed – typically a parametric curve-fit, neural network, Bayesian network, or a time-series trending of a precursor signal. This approach assumes that there are one or more expected usage profiles that are predictable and can be simulated, often in a laboratory setup. In some products the usage profiles are predictable, but this is not always the case.

For a fielded product with highly varying usage profiles, an unexpected change in the usage profile could result in a different (noncharacterized) change in the precursor signal. If the precursor reasoning model is not characterized to factor in the uncertainty in life-cycle usage and environmental profiles, it may provide false alarms. Additionally, it may not always be possible to characterize the precursor signals under all possible usage scenarios (assuming they are known and can be simulated). Thus, the characterization and model development process can often be time-consuming and costly, and may not always work.

There are many examples of the monitoring and trending of failure precursor to assess health and product reliability. Some key studies are presented below.

Smith and Campbell [57] developed a quiescent current monitor (QCM) that can detect elevated Iddq current in real time during operation.[2] The QCM performed leakage current measurements on every transition of the system clock to get maximum coverage of the IC in real time. Pecuh et al. [58] and Xue and Walker [59] proposed a low-power built-in current monitor for CMOS devices. In the Pecuh et al. study, the current monitor was developed and tested on a series of inverters for simulating open and short faults. Both fault types were successfully detected and operational speeds of up to 100 MHz were achieved with negligible effect on the performance of the circuit under test. The current sensor developed by Xue and Walker enabled Iddq monitoring at a resolution level of 10 pA. The system translated the current level into a digital signal with scan chain readout. This concept was verified by fabrication on a test chip.

GMA Industries [60–62] proposed embedding molecular test equipment (MTE) within ICs to enable them to test themselves continuously during normal operation and to provide a visual indication that they have failed. The MTE could be fabricated and embedded within the individual IC in the chip substrate. The molecular-sized sensor “sea of needles” could be used to measure voltage, current, and other electrical parameters, as well as sense changes in the chemical structure of ICs that are indicative of pending or actual circuit failure. This research focuses on the development of specialized doping techniques for carbon nanotubes to form the basic structure comprising the sensors. The integration of these sensors within conventional IC circuit devices, as well as the use of molecular wires for the interconnection of sensor networks, is a crucial factor in this research. However, no product or prototype has been developed to date.

Kanniche and Mamat-Ibrahim [63] developed an algorithm for health monitoring of voltage source inverters with pulse width modulation. The algorithm was designed to detect and identify transistor open-circuit faults and intermittent misfiring faults occurring in electronic drives. The mathematical foundations of the algorithm were based on discrete wavelet transform (DWT) and fuzzy logic (FL). Current waveforms were monitored and continuously analyzed using DWT to identify faults that may occur due to constant stress, voltage swings, rapid speed variations, frequent stop/start-ups, and constant overloads. After fault detection, “if-then” fuzzy rules were used for very large scale integrated (VLSI) fault diagnosis to pinpoint the fault device. The algorithm was demonstrated to detect certain intermittent faults under laboratory experimental conditions.

2 The power supply current (Idd) can be defined by two elements: the Iddq-quiescent current and the Iddt-transient or dynamic current. Iddq is the leakage current drawn by the CMOS circuit when it is in a stable (quiescent) state, and Iddt is the supply current produced by circuits under test during a transition period after the input has been applied. It has been reported that Iddq has the potential for detecting defects such as bridging, opens, and parasitic transistor defects. Operational and environmental stresses, such as temperature, voltage, and radiation, can quickly degrade previously undetected faults and increase the leakage current (Iddq). There is extensive literature on Iddq testing, but little has been done on using Iddq for in-situ PHM. Monitoring Iddq has been more popular than monitoring Iddt [57–59].

Table 1.4 Monitoring parameters based on reliability concerns in hard drives.

Reliability issues	Parameters monitored
• Head assembly – Crack on head – Head contamination or resonance – Bad connection to electronics module • Motors/bearings – Motor failure – Worn bearing – Excessive run-out – No spin • Electronic module – Circuit/chip failure – Interconnection/solder joint failure – Bad connection to drive or bus • Media – Scratch/defects – Retries – Bad servo – ECC corrections	• Head flying height: A downward trend in flying height will often precede a head crash. • Error checking and correction (ECC) use and error counts: The number of errors encountered by the drive, even if corrected internally, often signals problems developing with the drive. • Spin-up time: Changes in spin-up time can reflect problems with the spindle motor. • Temperature: Increases in drive temperature often signal spindle motor problems. • Data throughput: Reduction in the transfer rate of data can signal various internal problems.

Self-monitoring analysis and reporting technology (SMART), currently employed in select computing equipment for hard disk drives (HDDs), is another example of precursor monitoring [64]. HDD operating parameters, including the flying height of the head, error counts, variations in spin time, temperature, and data transfer rates, are monitored to provide advance warning of failures (see Table 1.4). This is achieved through an interface between the computer's start-up program (basic input/output system, BIOS) and the HDD.

Systems for early fault detection and failure prediction are being developed using variables such as current, voltage, and temperature continuously monitored at various locations inside the system. Along with sensor information, soft performance parameters such as loads, throughputs, queue lengths, and bit error rates are tracked. Prior to PHM implementation, characterization is conducted by monitoring the signals of different variables to establish a multivariate state estimation technique (MSET) model of the "healthy" systems. Once the healthy model is established using these data, it is used to predict the signal of a particular variable based on learned correlations among all variables [65]. Based on the expected variability in the value of a particular variable during application, a sequential probability ratio test (SPRT) is constructed. During actual monitoring, SPRT is used to detect deviations of the actual signal from the expected signal based on distributions (and not on a single threshold value) [66, 67]. This signal is generated in real time based on learned correlations during characterization (see Figure 1.9). A new signal of residuals is generated, which is the arithmetic difference of the actual and expected time-series signal values. These differences are used as input to the SPRT model, which continuously analyzes the deviations and provides an alarm if

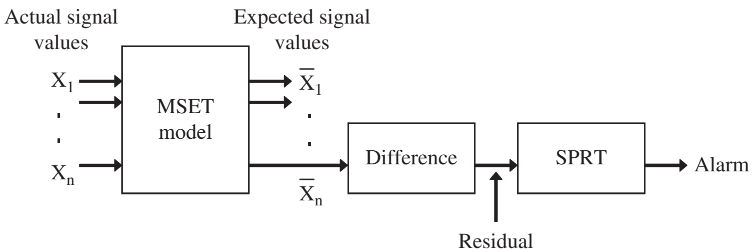

Figure 1.9 Sun Microsystems' approach to PHM.

the deviations are of concern [65]. The monitored data are analyzed to provide alarms based on leading indicators of failure and enable use of monitored signals for fault diagnosis, root cause analysis, and analysis of faults due to software aging [68].

Brown et al. [69] demonstrated that the RUL of a commercial global positioning system (GPS) can be predicted by using a precursor-to-failure approach. The failure modes for GPS included precision failure due to an increase in position error, and solution failure due to increased outage probability. These failure progressions were monitored in situ by recording system-level features reported using the National Marine Electronics Association (NMEA) Protocol 0183. The GPS was characterized to collect the principal feature value for a range of operating conditions. Based on experimental results, parametric models were developed to correlate the offset in the principal feature value with solution failure. During the experiment, the BIT provided no indication of an impending solution failure [69].

1.3.3.2 Data Analytics and Machine Learning

Data-driven approaches for PHM are used for both the diagnosis and prognosis stages, often based on statistical and machine learning techniques, as illustrated in Figure 1.10.

In Figure 1.10, data acquisition is to collect the data necessary for PHM, including operational and environmental data that can be obtained from sensors by selecting and appropriately locating sensors that provide the capability to collect a history of time-dependent degradation of materials or environmental stresses on a target product. In general, the first step of data-driven approach to PHM is data pre-processing, including missing value management, data cleansing (e.g. noise removal, outlier removal), normalization or scaling, imbalanced data management, and so forth.

The next step will be feature discovery to find a good set of features that can be used for anomaly detection, diagnosis, and prognosis. More specifically, feature discovery involves feature construction via time, frequency, and time–frequency analyses, dimensionality reduction based on either feature extraction or feature selection, and feature learning using deep neural networks to automatically discover the representations needed for feature detection and classification, typically related to diagnostic tasks in PHM. Note that feature extraction is to reduce the dimensionality of the given feature vector by using linear or nonlinear transformations, whereas feature selection is to select an optimal subset of the given feature vector for PHM tasks.

Representative feature extraction techniques include principal component analysis (PCA) [70], kernel PCA [71], linear discriminant analysis (LDA) [72], kernel LDA [73], generalized discriminant analysis [74], independent component analysis [75],

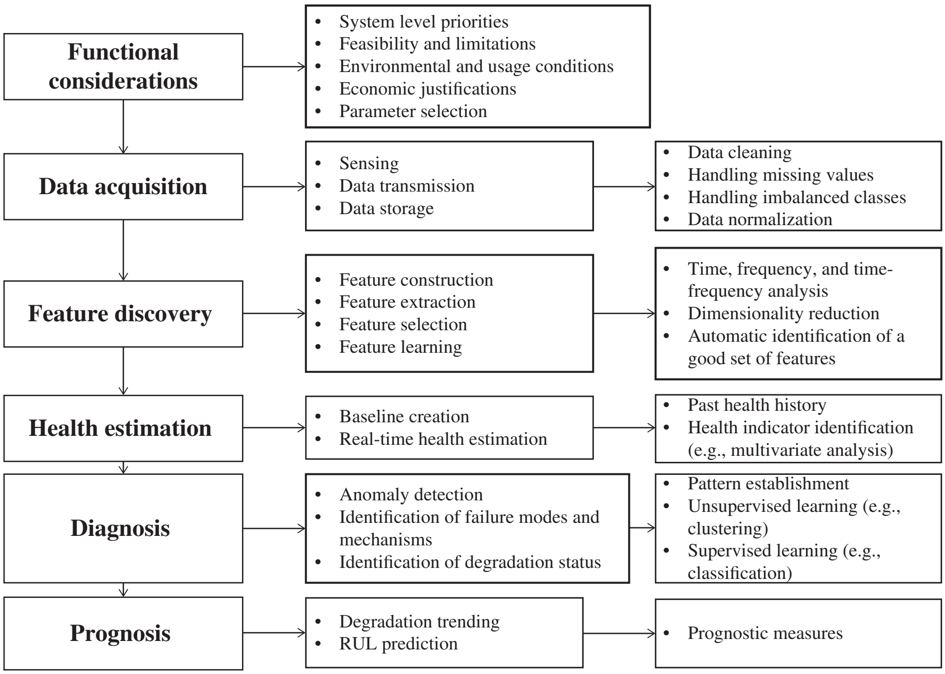

Figure 1.10 A general procedure of a data-driven approach to prognostics.

t-distributed stochastic neighbor embedding [76], and so forth. For feature selection, the following methods are representative: filter methods, wrapper methods, and embedded methods. Filter feature selection methods apply a statistical measure to assign a score to each feature. The features are ranked by the score and either selected to be kept or removed from a given dataset. The methods are often univariate and consider the feature independently, or with regard to the dependent variable. Some examples of some filter methods include the Chi-square test [77], information gain [78], and correlation coefficient scores [79]. Wrapper methods consider the selection of a set of features as a search problem, where different combinations are prepared, evaluated and compared with other combinations. A predictive model (e.g. k-nearest neighbor, support vector machines, and neural networks) is used to evaluate a combination of features and assign a score based on model accuracy. The search process may be methodical, such as a best-first search, it may be stochastic such as a random hill-climbing algorithm, or it may use heuristics, like forward and backward passes to add and remove features. An example of a wrapper method is the recursive feature elimination algorithm [80]. Embedded methods learn which features best contribute to the accuracy of the model while the model is being created. The most common type of embedded feature selection methods are regularization methods. Regularization methods are also called penalization methods, and introduce additional constraints into the optimization of a predictive algorithm (such as a regression algorithm) that bias the model toward lower complexity (fewer coefficients). Examples of regularization algorithms are the least absolute shrinkage and selection operation (LASSO) [81], elastic net [82], and ridge regression [83].